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1. INTRODUCTION

There is a general perception among transportation engineers that is shared among many professionals that have utilized aerial photography that high resolution remote sensing images from space-based systems at less than 10 meters to submeter scale would enhance their ability to accomplish work-related tasks. Although the resolution of satellite imagery is not comparable to aerial photography, the fact that these images can be acquired repeatedly and in a timely manner is certainly deemed an advantage. Furthermore, the fact that the images are digital and multispectral in nature opens the possibility that the images can be manipulated mathematically and classified in a systematic and repeatable procedure. It is imperative that one has a clear idea as to what information they wish to extract from imagery so that these goals can be matched to the appropriate data set. Each image data set has its advantages and disadvantages. Classification of high resolution imagery is not as straightforward as more traditional classification with lower resolution imagery (30 m or more).

The challenges of classifying high resolution imagery stems primarily from two attributes. First, the classification system must be vastly more detailed than traditional classification systems because the spectral response of each pixel is associated with very specific earth and man-made materials. There is no inherent generalization as in low resolution imagery. Typically, we are not interested in such high levels of classification detail and some degree of generalization is desired in the end. Secondly, while the small pixel size dictates a fairly high degree of classification specificity, the spectral resolution of high resolution sensors is limited to only four bands thereby limiting one's ability to discriminate among materials. Such low spectral resolution makes it difficult to distinguish many earth and man-made materials. Thus, a careful balance must be sought between the number of classes defined and the ability to discriminate among them. Failing to strike the correct balance means that you can end up with classes that have broad spectral characteristics so they cannot be reasonably distinguished from other classes. In the end, we may require several classes of asphalt road, but still find it rather difficult to distinguish some of these road classes from rooftops of structures that are comprised of very similar materials.

In this activity, imagery over the same target from three different sensing systems is classified to illustrate the different capabilities of data from these systems. These data also illustrate some of the challenges one faces in classifying high resolution imagery of an urban environment. We classify a portion of a Landsat ETM+ scene, Advanced Thermal Land Applications Sensor (ATLAS) scene and a QuickBird-2 scene. The acquisition dates and resolution of these data sets is given in the table below.

Table 1. Specifications for imagery used in this activity.

Sensing System	Acquisition Date	Resolution (m)	No. of Bands	Spectral Range (μm)
Landsat ETM+	April 5, 2000	28.5	7	0.45-12.5
ATLAS	May 11, 1997	10	14	0.45-12.2
QuickBird-2	March 10, 2002	2.4	4	0.45-0.88

2. IMAGERY

The Landsat series of satellites provide one of the most extensive and continuous terrestrial imagery archives. Since the beginning of the Landsat program in 1972, data have been acquired from three different generations of sensors, the Multispectral Scanner (MSS), Thematic Mapper (TM) and Enhanced Thematic Mapper Plus (ETM+). Landsat imagery of the globe is subset and marketed as a patchwork of individual scenes identified by a row and path designation. The MSS was a 4-channel sensor that is no longer operational, however, archived historical data are available. The TM and ETM+ are 7 channel multispectral sensors. ETM+ also includes a broadband panchromatic channel. The visible and infrared channels of TM and ETM+ are nominally 28.5 m resolution, whereas the thermal channel is 90 m resolution on TM and 60 m resolution on ETM+.

ATLAS was flown on board a Lear 23 jet aircraft operated by NASA Stennis Space Center. The ATLAS is a 15-channel multispectral scanner that incorporates the bandwidths of the Landsat TM and ETM+ with additional bands in the middle reflective infrared and thermal infrared range. ATLAS data were collected at an altitude of approximately 5,032 m above mean terrain, which resulted in an image spatial resolution of 10 m. Images from each north-south trending flight line were rectified with approximately 100 ground control points each.

In the United States, high resolution satellites reside in the commercial sector. Examples include the IKONOS instrument owned and operated by Space Imaging, Orbview-3, operated by ORBIMAGE, and the QuickBird-2 instrument operated by Digital Globe. The IKONOS -2 satellite was launched in September 1999 and has been delivering commercial data since early 2000. IKONOS is the first of the next generation of high spatial resolution satellites. IKONOS data records 4 channels of multispectral data at 4 meter resolution and one panchromatic channel with 1 meter resolution. Orbview-3, launched in June 2003, has similar characteristics to IKONOS. ORBIMAGE is planning to launch a higher resolution satellite in 2007. QuickBird-2, launched in October 2001, has four channels with equivalent spectral properties as Landsat's visible and near infrared channels 1 to 4. These data are acquired at 2.4 m resolution, the highest of all civilian satellite-based sensors to date. In addition, QuickBird has a panchromatic sensor with 0.61 m resolution. QuickBird-2 data is used in this activity.

PART I

Land Cover Classification of an Urban Watershed with ATLAS Imagery

3. SOPE CREEK WATERSHED

The Sope Creek watershed is a highly urbanized watershed on the northern edge of Marietta, Georgia, just north of the Atlanta Metropolitan area (Figures 1 and 2). This is a rapidly growing area that has preserved ecological diversity and natural water resources in the midst of urbanization. The Sope Creek was selected as a challenging land cover and land use classification project as the watershed has a diverse combination of urban features for which high resolution multispectral remote sensing data were available. Also, the watershed's close proximity to major transportation arteries and the availability of remote sensing and existing land use data were primary considerations.

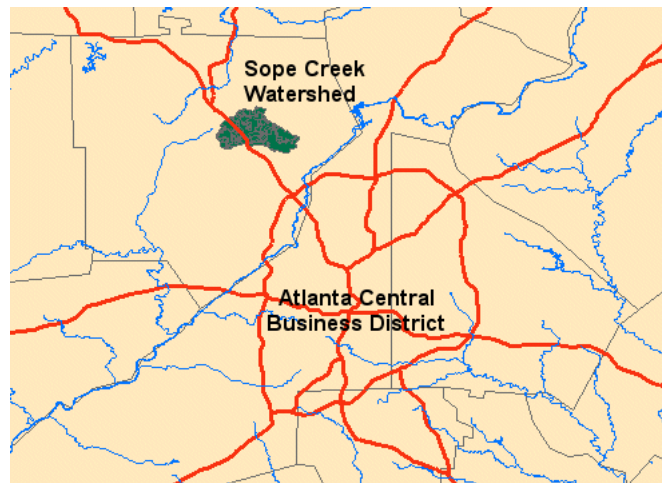


Figure 1. Map showing the location of Sope Creek watershed along Interstate-75 northwest of downtown Atlanta.



Figure 2. True color image of the Sope Creek watershed.

Land cover for the Sope Creek watershed was classified using high spatial resolution (10 meter) multispectral (15 bands) remote sensing imagery from an airborne sensor, the Advanced Thermal Land Applications Sensor (ATLAS). ATLAS is a 15-channel multispectral scanner that possesses the same bandwidths as the space borne Landsat Thematic Mapper (TM) instrument and additional bands in the middle reflective infrared and thermal infrared (TIR) range that is flown on a Lear 23 jet aircraft operated by NASA.

The 10 m spatial resolution permitted the discrimination of discrete surface types (e.g., concrete, asphalt) as well as individual structures (e.g., buildings, houses). Moreover, TIR data collected with the ATLAS at high spatial resolution are particularly important for providing fine scale resolution of individual surfaces from which the thermal energy responses characteristic of these surface can be derived. These data have been extremely useful for providing quantitative information on what the thermal attributes are of the urban landscape, as well as what the distribution is of thermal energy responses. Additionally, the employment of high spatial resolution TIR data for analyses of surface thermal responses is both innovative and unique, and offers research and application capabilities that have proven to be extremely useful for developing a better understanding of how urban surface heating affects UHI development (see Quattrochi and Ridd, 1994, Lo et al., 1997, Quattrochi and Ridd, 1998, Quattrochi and Luvall, 1999).

A classification of land use is not a direct aggregation of land cover classes. For example, grass, a typical land cover class, can be associated with golf courses, recreational parks, cemeteries, residential lawns, or surround commercial buildings. To convert land cover maps to land use maps requires additional ancillary data and processing. For this purpose, we utilized the LandPro99 dataset, a collection of land use classes compiled for the Atlanta Regional Commission. The classification is a vector product with 28 classes. These data were used to define training data for guidance in reclassification of the image for land use classes.

4. REMOTE SENSING IMAGERY

The effects of atmospheric path radiance and transmittance were corrected for to permit accurate analyses of thermal energy responses from ATLAS' TIR data (cf. Anderson and Wilson; 1981; Quattrochi and Goel, 1995; Quattrochi and Luvall, 1999). In order to correct for atmospheric effects, it is necessary to know what the structure of the atmosphere is through measuring various atmospheric characteristics. This information for input into atmospheric correction algorithms is obtained from atmospheric soundings, launched during the time of TIR data acquisition that records data on humidity (dew point), temperature, barometric pressure, and height above the ground. Hence, these weather balloon data provide a profile of the atmosphere between the ground and the airplane that are in turn, used as input into computer models that correct for atmospheric effects on TIR data. Sounding data were obtained commensurate with ATLAS data collection.

LOWTRAN6 has been shown to provide robust results in modeling out atmospheric path radiance and transmission, the primary constituents that effect the derivation of accurate measurements from TIR data. The output from LOWTRAN6 is combined with calibrated ATLAS spectral response curves and blackbody information recorded during the overflight, using the Earth Resources Laboratory Applications Software (ELAS) module TRADE (TIMS

RADiant Energy) (Graham et al., 1986) to produce a look-up table for pixel temperatures as a function of ATLAS values (Anderson, 1992). A noise equivalent delta temperature (NE Δ T) was then calculated for each channel from image "housekeeping" data. NE Δ T is a measure of the energy of that input radiation falling on the sensor detector that would give an output signal equal to the noise generated by the detector. The smaller the NE Δ T value, the better the detector (Anderson and Wilson, 1984). A NE Δ T of 0.2 was obtained for ATLAS channel 13 (9.6-10.2 μ m, centered at 10 μ m) used in the analysis of data for Atlanta.

Data processing and calibration were performed using the ELAS software. Flight lines of ATLAS TIR data for each city were first pre-processed to remove any abnormalities present in the data (e.g., dropped scan lines). Each flight line of ATLAS TIR data was then run through the TRADE algorithm to produce an atmospherically corrected data set. All of the ATLAS TIR multispectral data sets collected for Atlanta were then georeferenced to UTM map coordinates to produce a geometrically corrected data set for each city. These processes ensured the generation of the high quality data sets that have been used to calculate accurate surface temperatures for a variety of surface types, to produce a land cover classification, to derive thermal color and true color map products, and to provide a data set that can be imported into geographic information systems and used for further analysis.

5. LAND COVER CLASSIFICATION

The Land cover classification was performed with ENVI 4.0 software using the supervised parallelepiped technique. This is a standard technique readily available for use by transportation professionals. Parallelepiped classification uses simple decision rules that define boundaries based on standard deviation thresholds from the mean of each class to classify multispectral data. Bands 4 (visible), 6 (near infrared), and 13 (infrared) were used to develop the land cover classification. Polygons with a minimum of 500 pixels per land cover class were selected training. The total number of pixels in training polygons among all classes ranged from 657 to 4,356 and comprised approximately one percent of all pixels in the Sope Creek watershed. The Sope Creek watershed spans two flight lines of ATLAS data. Each flight line was classified separately and then mosaicked to produce the land cover classification product (Figure 3 , Table 2).

These classes are consistent with the heavily vegetated character of the study area. The majority of the low-density residential areas are comprised of forest and grass classes. Low-density residential rooftops comprise a significant portion of the unclassified pixels too. Urban areas have been classified into low albedo and high albedo areas. The high albedo areas are primarily light building roofs and concrete surfaces. Low albedo areas are represented by asphalt surfaces on roads and parking areas plus dark building roofs. Land areas in transition for urban development comprise most of the bare soil class.

Overall, the results are a good representation of the physical surface of the Sope Creek watershed. Some mixed pixels between the high albedo urban and bare soil class remain a problem. The mature forest canopy made identification of urban features challenging, especially in areas remote from urban concentrations. Also, with more detailed ground truth data a delineation of evergreen forest areas from the predominant deciduous forest could have been evaluated.

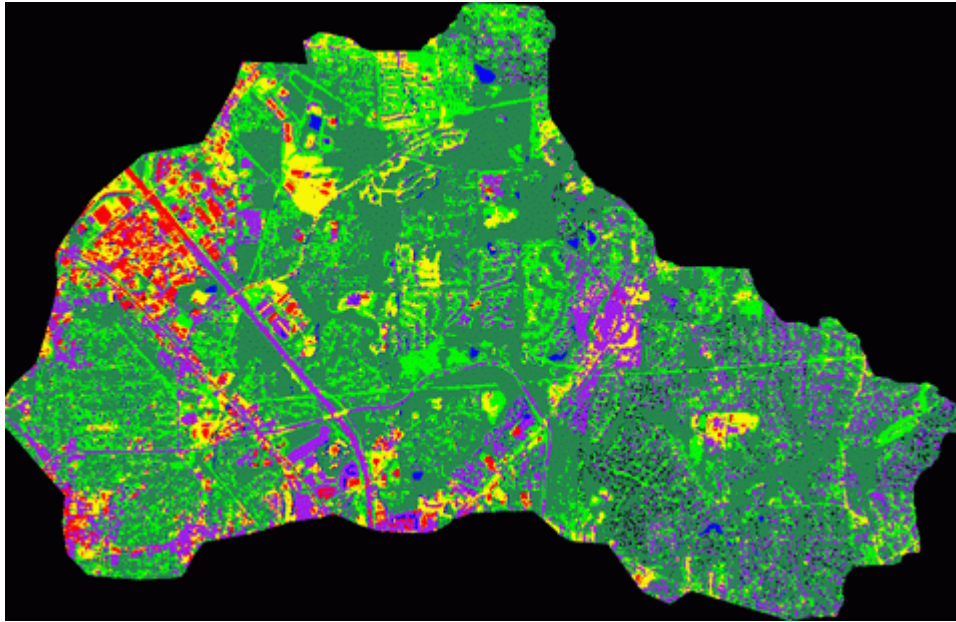


Figure 3. Land cover classification of Sope Creek watershed based on the Advanced Thermal Land Applications Sensor (ATLAS) airborne remote sensing instrument.

Table 2: Area of each class within the Sope Creek watershed estimated from image classification.

Color	Class	Percent of Watershed
dark green	forest	42.0
light green	grass	25.1
purple	urban-low albedo materials	17.1
red	urban-high albedo materials	3.7
yellow	bare soil	9.4
blue	water	1.4
black	unclassified	1.3

6. LANDPRO99 DATASET

LandPro99 is a land use/land cover dataset developed by the Atlanta Regional Commission (ARC) for the 13-county Atlanta metropolitan region. The LandPro99 dataset was created by photo interpretation of color aerial photography at four-foot pixel resolution and color infrared digital orthophoto quarter quads with one-meter pixel resolution provided by the U.S. Geological Survey (USGS). Using both sources of imagery, landcover polygons were delineated. Land use was added after the landcover was completed and is based primarily on property ownership information available in the Region. The land use/land cover classification system is adapted from the USGS Anderson system and includes a total of 28 classes. These data were used to define training data for guidance in reclassification of the image for land use classes.

Within the Sope Creek study area, the LandPro99 dataset contained seventeen land use classes. These classes were available in vector format and provided an optimal data source for use in developing training classes to produce an automated land use class from the remotely sensed ATLAS data source. The LandPro99 land use classes are defined as follow with abbreviations as noted on the map legend describe in parentheses:

Medium Density Residential (Res_Med): Areas that have generally been developed for single-family residential use, with or without a significant mix of forested or agricultural landcover.

High Density Residential (Res_High): Areas that have predominately been developed of concentrated single-family residential use, usually found in urban neighborhoods.

Multi-family Residential (Res_Multi): Residential areas comprised predominately of apartment, condominium, and townhouse complexes where net density generally exceeds eight units per acre.

Commercial and Services (Commercial): Areas used predominately for the sale of products and services, including urban central business districts, shopping centers in suburban and outlying areas, commercial strip developments, junk yards and resorts.

Industrial/Commercial (Ind/Com): Industrial and commercial areas that typically occur together or in close functional proximity with one another.

Transportation, Communication, and Utilities (TCU): Various land use types associated with transportation, communication, and utilities such as electrical substations, pumping stations, and airwave communications.

Institutional-intensive (Inst_Intensive): The built-up portions of institutional land holdings, including all building, grounds and parking lots that compose educational, religious, health, correctional and military facilities.

Cemeteries (Cemeteries): Public and private lands devoted to burial grounds, including primary and secondary buildings and associated infrastructure.

Golf course (Golf_Courses): The "green space" areas of golf courses, including tees, fairways, greens and intervening land.

Parks (Parks): Active recreation areas identified from aerial photography, including baseball and other sports fields, tennis courts, swimming pools, camp grounds, parking lots, structures, drives, and trails.

Agriculture Crops and Pasture (Ag_Crops): Agricultural land regularly used to grow field crops or to pasture animals.

Forest (Forest): All forested areas of coniferous and/or deciduous trees.

Urban Other (Urban_Other): Open land in intensive or indeterminate urban uses that do not require or do not have structures.

Limited Access (Ltd_Access): All highways or portions of highways that are considered "limited access", their right-of-ways, ramps and interchanges.

Transitional (Transitional): Recently cleared or altered land in transition from one land use activity, either built-up or non-built-up, to another unknown or undeterminable land use.

Reservoirs, Lakes, and Ponds (Reservoirs): Man-made impoundments often referred to as "lakes or "ponds", which are persistently covered with water.

Bare Exposed Rock (Exposed_Rock): Naturally occurring areas of exposed bedrock with little or no vegetative cover.

7. LAND USE CLASSIFICATION

The major objective of this task is to evaluate the utility of remotely sensed multi-spectral data for urban land use classification in major transportation corridors. ATLAS multi-spectral 10-meter data was used to perform the Sope Creek land use classification with ENVI 4.0 software. Polygons matching Landpro99 land use classes were selected as training classes.

Standard supervised classification algorithms including parallelepiped, maximum likelihood, and minimum distance were evaluated for use in this study. All these algorithms are standard techniques readily available for use by transportation professionals. Parallelepiped classification uses the threshold of each class signature to determine if a pixel is within a class or not (J.A. Richards, 1994, *Remote Sensing Digital Image Analysis*, Springer-Verlag, Berlin, p. 340). Advantages are speed and potential problems are low accuracy if a large number of pixels cannot be classified. The maximum likelihood classifier uses the Gaussian threshold in each class signature to determine the pixel's class. The maximum likelihood technique is slower compared to parallelepiped technique due to extra computations required, however, results may be more accurate if classes in the input data have a Gaussian distribution. Finally, the minimum distance algorithm compares distances between the pixel to be classified and each class center and the pixel is assigned to the nearest class center. For this study, the parallelepiped classifier was used. The advantage of a Gaussian distribution in classes was not evident in preliminary classifications thereby limiting the advantages offered by the maximum likelihood classifier and the wide variation in class sizes was a factor in not selecting the minimum distance algorithm. The parallelepiped technique resulted in a low percentage of unclassified pixels, alleviating a common concern when utilizing this classifier.

Because each study area has a unique combination of physical features and surface types, testing is necessary to identify the spectral bands that carry the majority of the information given the spectral and spatial resolution of the available remote sensing data. For the Sope Creek study area with ATLAS data, we determined that bands 3 (visible), 6 (near infrared), and 13 (infrared) were sufficient to develop the final landcover classification.

Land use compared to land cover classification presents some unique problems. The land use classes represent a mixture of land covers with varying spectral signatures, which makes classification of land uses more difficult. For example, the *Low-density Residential* land use class is comprised of a mixture of surface types (i.e. land covers) including grass, forest, concrete, and asphalt materials. Commercial and industrial land uses typically contain concrete, asphalt, and grass interspersed with small forest stands. These "mixed pixel" classes limit the ability of standard classifiers to accurately characterize some land use types. As a result, more specific land use classes must be aggregated into a more generalized class. For example, *Multi-family*, *High-density Residential*, and *Institutional* classes may have similar spectral features as *Commercial* and *Industrial* classes and be considered part of such classes. Also, grass and selected recreational areas such as parks and golf courses may be considered part of the *Low-density Residential* land use class.

Another limitation that stems from using standard classifiers to produce land use classes from multi-spectral data is the small spatial extent of some of the land use classes in the Sope Creek region. This impacted classes with less than 5,000 total pixels, such as *Parks/Recreation*, *Limited Access*, *Cemeteries*, and *Transitional*. The heavily shaded character of the study areas also

presented classification challenges in the interpretation of spectral signals in these areas (ATLAS data were processed for geometric, atmospheric, and shadow corrections prior to use in this study).

Land use classification produced four classes as shown in Figure 4 and Table 3. Although the LandPro99 data set identified 17 land use classes within the Sope Creek watershed, due to mixed pixel challenges and the small extent of some classes as noted above, only a rather generalized classification with three principal classes and a small percentage of unclassified pixels could be achieved. A number of land use classes simply were not spectrally unique. Ultimately, LandPro99 *Forest* and *Cemeteries and Transitional* classes were combined as the *Forest* class. *Commercial and Services*, *Industrial/Commercial*, *Reservoirs*, *Lakes*, and *Ponds*, *Transportation*, *Communication*, and *Utilities* (TCU) were aggregated as *Commercial/Industrial*. *Medium Density Residential* was significantly unique and in large enough spatial extent to be isolated as *Residential*.

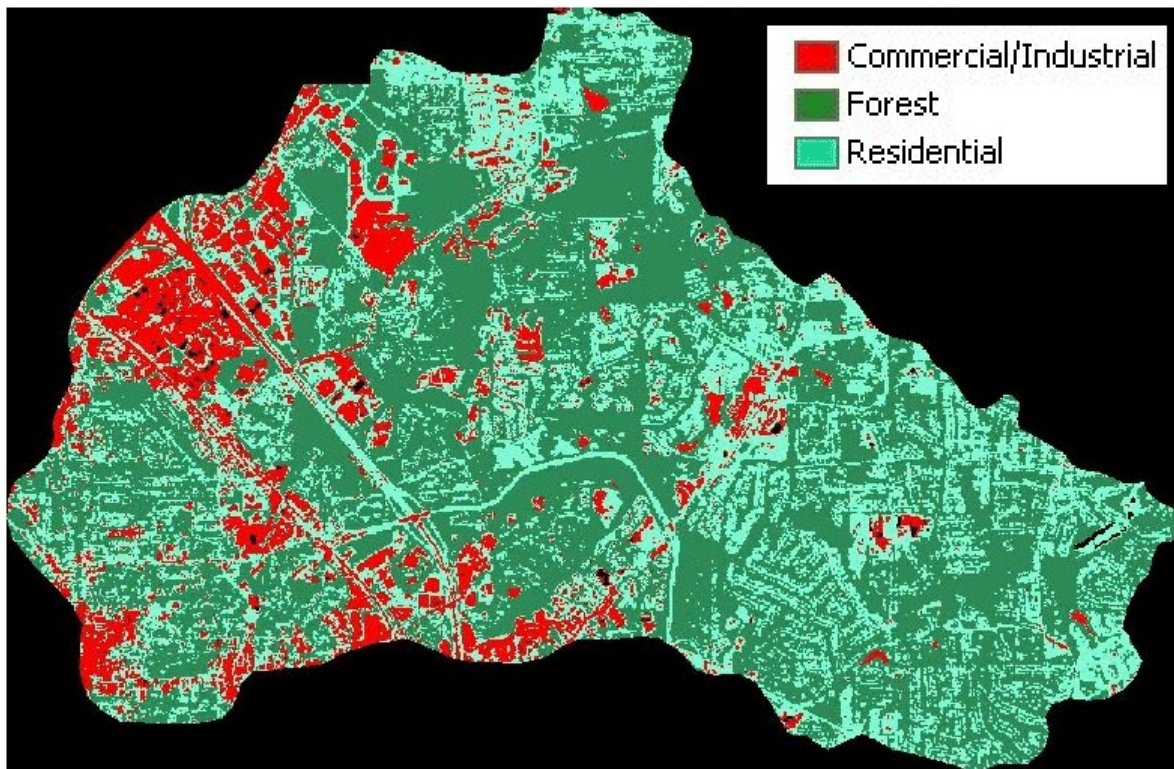


Figure 4. Land use classification of Sope Creek watershed.

Table 3: Results from Land Use Classification

Class	Color	Number of Sample Pixels	Number of Class Pixels	% Area of Class
Forest	sea green	9098	284647	53
Low Density Residential	aquamarine	8960	181446	33
Commercial/Residential	red	7415	73039	13
Unclassified	black	0	3384	1

The *Forest* class is a significant land use in the region. The *Cemeteries* and *Transitional* classes were too heavily forested to be spectrally unique resulting in being grouped with the *Forest* class. This, of course, is unique to this area with older, more established cemeteries. The urban core of industrial and commercial development is consistently captured in the *Commercial/Industrial* class. The one area identified as TCU in the area is primarily urban with very little vegetation in the class, so it also is accurately classified. Due to the low albedo of lakes and ponds, these small manmade water bodies also provide spectral signatures that result in being combined in the *Commercial/Industrial* class. In many instances, this is an inaccurate association as most of these water bodies are found in residential areas in the Sope Creek region. The majority of the Sope Creek region is in single-family or low-density residential development that corresponds well to the *Medium Density Residential* land use class that encompasses the majority of the study area. There is some inclusion of forest areas in the residential class where dense tree growth occurs.

Bare Exposed Rock, Limited Access, Institutional-intensive, Agriculture Crops and Pasture, Golf Course, High Density Residential, Urban Other, Parks, and Multi-family Residential land use classes, were not consistently represented in the major land use classes delineated above. Most of these classes, with the exception of *Institutional-intensive* and *Multi-family Residential*, are very small in extent and often in one location. The *Institutional-intensive* and *Multi-family Residential* classes are typically confused with the *Commercial/Industrial* class due to the high percentage of common surface types. However, areas in these classes with significant vegetation tend to classify as *Residential* resulting in a mixture of pixels in these land use classes. Possibly with more evaluation and the use of advance textural classifiers, a *Multi-family Residential* class could be delineated. *Limited Access* classes tended to be classified as commercial in highly developed areas with asphalt surfaces and as residential in less developed areas especially with a high percentage of concrete and vegetative surfaces. Only one location each of *Bare Exposed Rock, High-density Residential, Agriculture Crops and Pasture, and Golf Course* classes were found in the study area, making evaluation of these areas impractical. With the opportunity to develop training classes, it is likely the *High-density Residential* class would be grouped with the *Commercial/Industrial* class described above. Development of unique classes for golf courses and some agricultural areas may also be possible.

Overall, the result is a good generalized representation of the major land use classes in the Sope Creek watershed. Further evaluation and the use of more advanced textural classifiers would likely enable two to three additional land use classes to be delineated.

PART II

Land Cover Classification of an Urban Residential Area with Different Resolution Imagery

8. INTRODUCTION

In this activity, imagery over the same target from three different sensing systems is classified to illustrate the different capabilities of data from these systems. These data also illustrate some of the challenges one faces in classifying high resolution imagery of an urban environment. We classify a portion of a Landsat ETM+ scene, Advanced Thermal Land Applications Sensor (ATLAS) scene and a QuickBird-2 scene. The acquisition dates and resolution of these data sets is given in Table 4.

Table 4. Specifications for imagery used in this activity.

Sensing System	Acquisition Date	Resolution (m)	No. of Bands	Spectral Range (μm)
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QuickBird-2	March 10, 2002	2.4	4	0.45-0.88

9. SEGMENTATION

Segmentation is an important pre-processing step before attempting to classify imagery. It is a subjective process whereby individual pixels are grouped with adjacent ones based on spectral similarity as well as shape criteria. The image analyst defines a scale parameter and three homogeneity criteria: shape factor, compactness and smoothness. All of these parameters are varied iteratively until the segmentation process yields a grouping of pixels that is meaningful to the analyst. In so doing, the image processing time is reduced because the mean of the segment object is used in subsequent analysis and there are fewer objects than pixels to processes. In addition, the homogeneity criteria serves as a first order filter on noise within a class because future processing is based on the mean of the grouping of pixels that make up a segment rather than on the individual pixels values. At the finest scale, these objects may represent discrete features, such as a house or car, or objects comprised of the same materials, such as asphalt, tree canopy, grass lawns, etc.

eCognition Professional (v. 4.2) was used for segmentation and classification in this activity. Figure 5 is an example of a software dialog box that allows the image analyst to specify scale and homogeneity criteria. In addition, each image band can be weighted individually as to their importance in influencing the outcome of the segmentation processes. Here, it would be desirable to reduce the weight of relatively noisy bands or bands that have little spectral contrast. On the other hand, a band with noise may help to differentiate classes and therefore be desirable if the noise is restricted to particular classes.

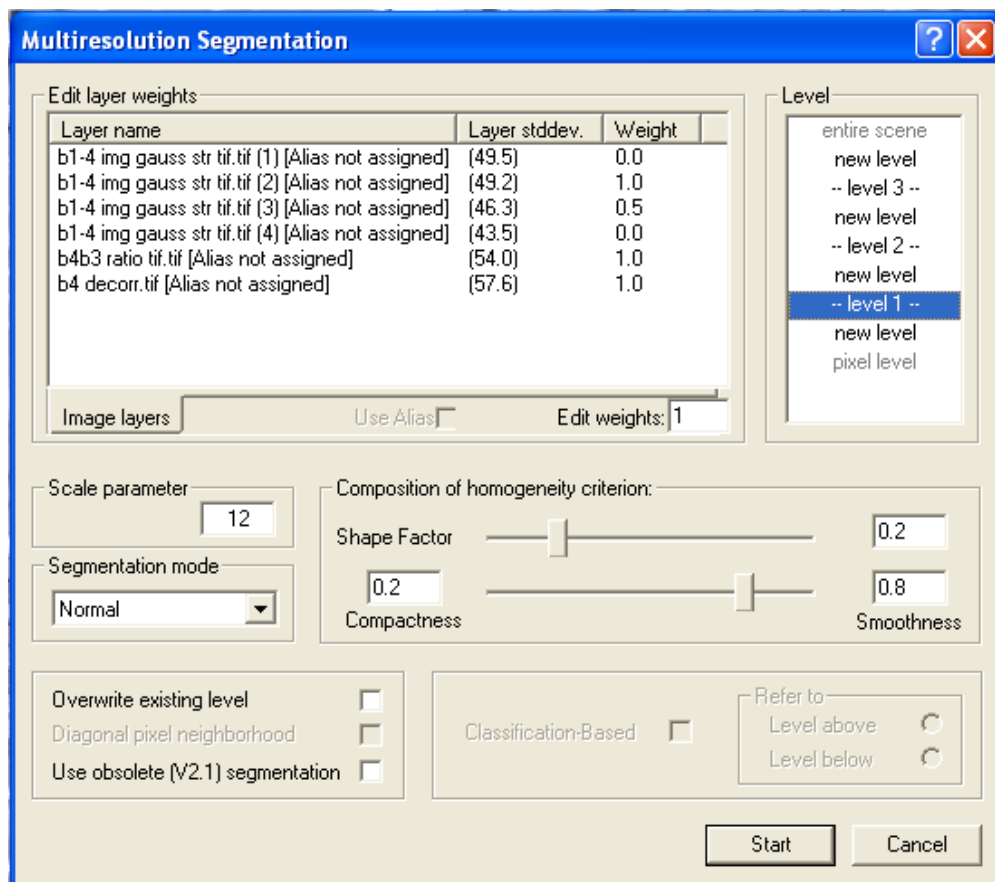


Figure 5. Segmentation dialog box used to specify scale and homogeneity criteria.

The notion of image “objects” is by its very nature a function of scale and thus highly dependent on image resolution. After all, objects are a collection of pixels that differentiate from their surroundings. In traditional classification with coarse resolution imagery (30 m to 1 km), we tend to think of objects as equivalent to classes, such as woodland, water, cropland. As resolution increases, objects tend to differentiate from classes. For example, objects might be represented by buildings, which taken collectively, might be classified as a commercial district. At even higher resolution, objects dissolve into materials with different spectral properties. Although this scale may appear more “realistic” to the human brain, the resolution may be too high to obtain meaningful objective interpretation through image processing. Multiscale segmentation offers a way to circumvent this problem by grouping pixels into objects of different size that can be interpreted. In addition, the objects can be further clustered into meaningful groups that can be classified.

Below is a subset of imagery for the same spatial domain from Landsat ETM+, ATLAS, and QuickBird (Figure 6). The spatial resolution of the QuickBird image (532 x 609) is approximately an order of magnitude greater than the ETM image (45 x 51). In this image of an urban residential area, the layout of roads can be seen in the ATLAS image at 10 m resolution. We can interpret from the patterns we see along the roads that there are houses. It is unclear to us from the ATLAS image alone whether the somewhat “noisy” pattern of houses is due to insufficient resolution of possibly tree canopy obscuring portions of each house. In the center of

the image, we can also detect a large building surrounded by green space and associated with a large oval. It is not difficult to interpret this as a school and track. In the full size version of the Quickbird image, the level of detail is much greater and we can readily see a baseball field between the school building and track and tennis courts. Not only is the outline of individual houses also visible, but the shadow cast by the houses is also discernible. In contrast, very little information is interpretable from the ETM image. Because the scale of discernible objects is much greater, a much larger portion of image is required to recognize features and objects.

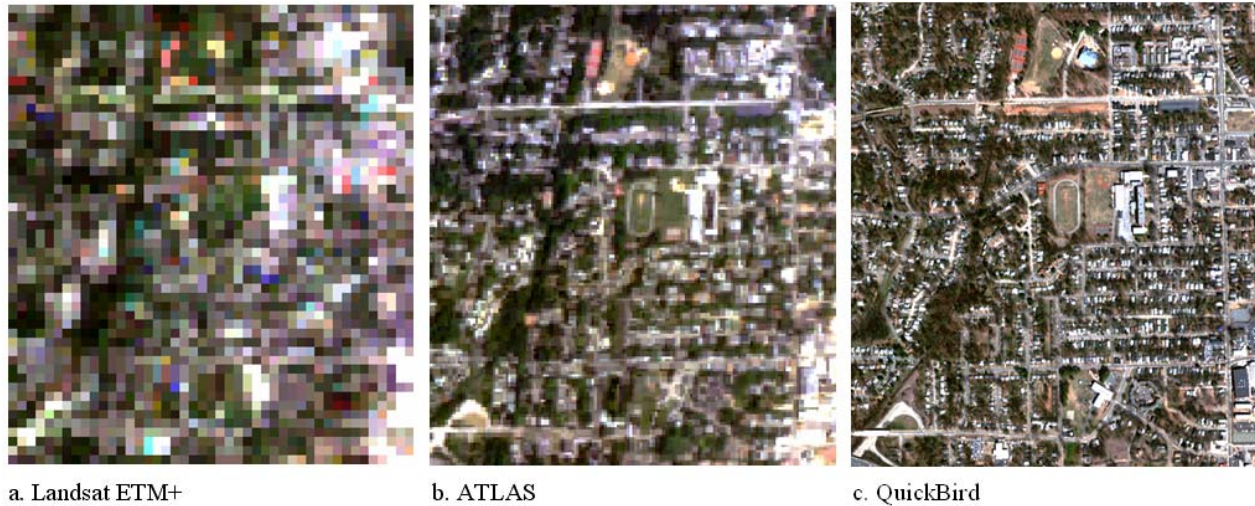


Figure 6. Portions of imagery for the same location from a. Landsat ETM+, b. ATLAS and c. QuickBird. As image resolution increases, the scale of objects that is readily discernible decreases.

Figure 7 shows a portion of QuickBird imagery showing a school and associated athletic fields surrounded by a residential area. Figure 8 is the resulting segmentation. The objective of this initial segmentation is to restrict the size of the segments to closely correspond to the size of primary objects of interest, in this case individual houses. In many cases, the houses are comprised of more than one segment, but increasing the segment scale even slightly caused much of the adjacent yard or shadows surrounding the house to be included in the segments. Thus, a delicate balance was established. On the other hand, creating such small segments means that large contiguous surfaces of grass or forest seem to have an excessive number of segments. This situation can be remedied utilizing a multiresolution classification based segmentation. Secondary segmentation can cluster first order segments of similar attributes into larger groups. Segments can be classified at the appropriate scale and then combined for the final classified image.

10. CLASSIFICATION

Taking into consideration the discussion above about object scale as a function of image resolution, a progressively larger subset of images was extracted for classification (Figure 9). Each of these images was acquired in the early springtime while the turf grasses were still senescent and before leaves emerged from trees and shrubs. Availability of both wintertime and springtime imagery would have yielded a better results, but such imagery was not available.



Figure 7. A portion of QuickBird imagery near Atlanta, GA, used in discussion about segmentation. This image was acquired March 10, 2002; there are no leaves on the trees at this time of year.



Figure 8. Segmentation at the finest scale where the smallest discernible objects, houses, are distinguished from surrounding surfaces.

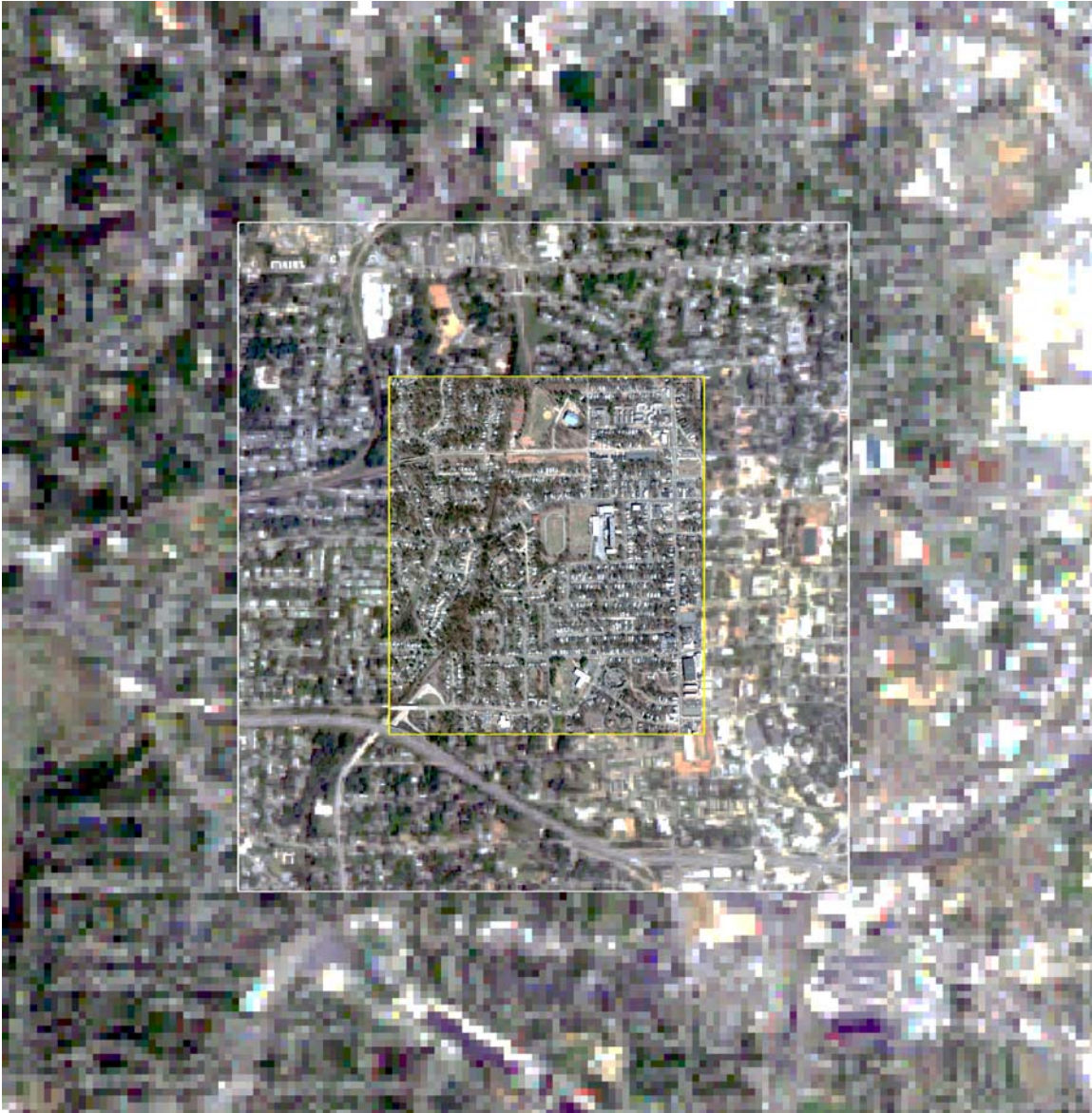


Figure 9. Imagery from Landsat ETM+ (largest image), ATLAS (intermediate image) and QuickBird (smallest image) are overlain in this mosaic to show the differences in image size appropriate for the object scales necessary to satisfactorily classify each image.

The ETM image is comprised of 181 x 173 pixels covering approximately 5 x 5 km. The six visible and infrared bands at 28.5 m resolution were used on the classification. The coarse resolution thermal band was not used in the classification. Figure 10 shows the resulting classification. The built up areas in this image could not be well discriminated in terms of objects. Thus, they tend to get lumped together in one large Urban/Transportation/Commercial/Industrial class. Residential density also could not be discerned from areas with either higher density or simply larger trees. Woodland was the only Undeveloped class and image resolution was insufficient and the woodland stands too small to distinguish deciduous from evergreen trees. Nonetheless, if your primary interest was in distinguishing highly developed commercial land from residential and non-residential, ETM data would be adequate for the task.

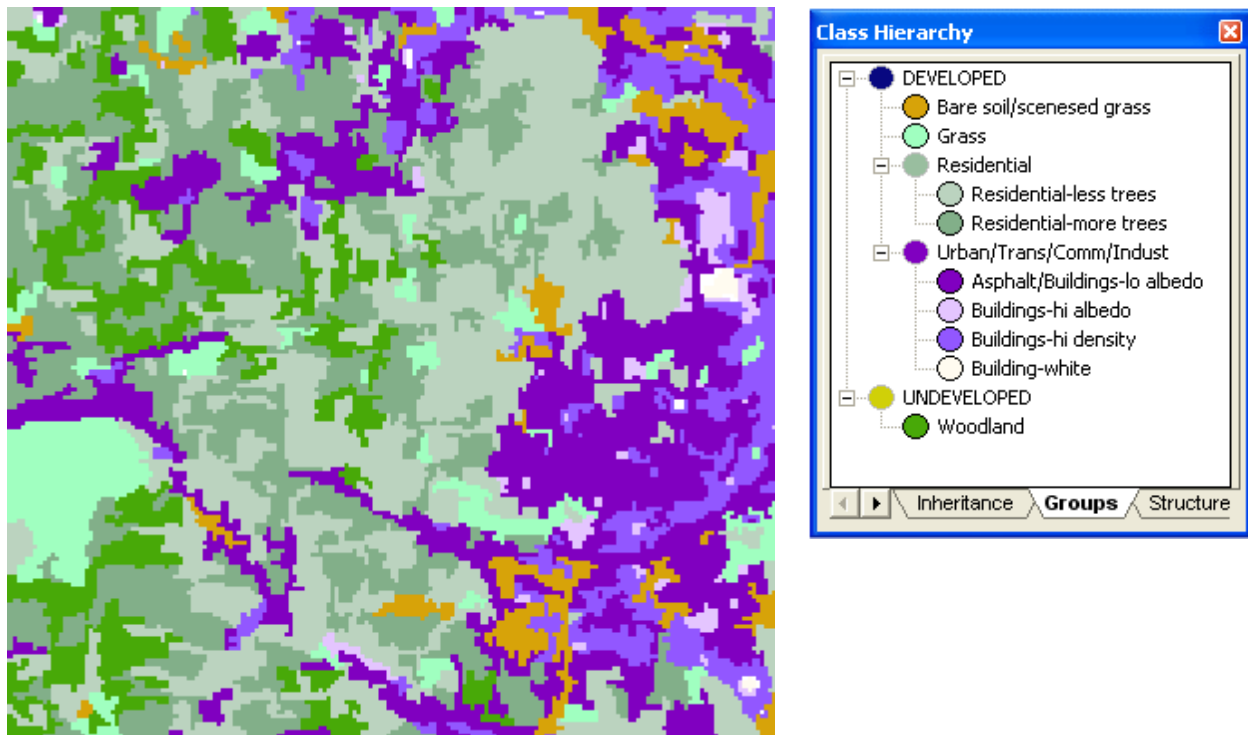


Figure 10. Land cover classification of Landsat ETM+ imagery.

The ATLAS image is comprised of 312 x 342 pixels covering 3.1 x 3.4 km. Technically speaking, ATLAS has higher spectral resolution than ETM as well as better spatial resolution. However, Band 9 of ATLAS was not functioning, and there is very little difference among the five thermal channels between 8.2 and 12.5 μm . In order to maximize the information among these channels, one could perform a decorrelation stretch on three of these channels and use the result in the classification. At the higher resolution, the tree canopy in the residential area has a more significant influence on the spectral properties of the area (Figure 11). It is incorrect to consider these areas as woodland and “undeveloped.” But an attempt was made to carry forward as many of the classes from the ETM classification as possible for sake of comparison. It would be best to impose an area scalar on this class to identify truly undeveloped land. At this resolution, major roads several lanes wide are detectable as are houses and buildings. The segmentation scale used, however, was too coarse to define individual houses for classification.

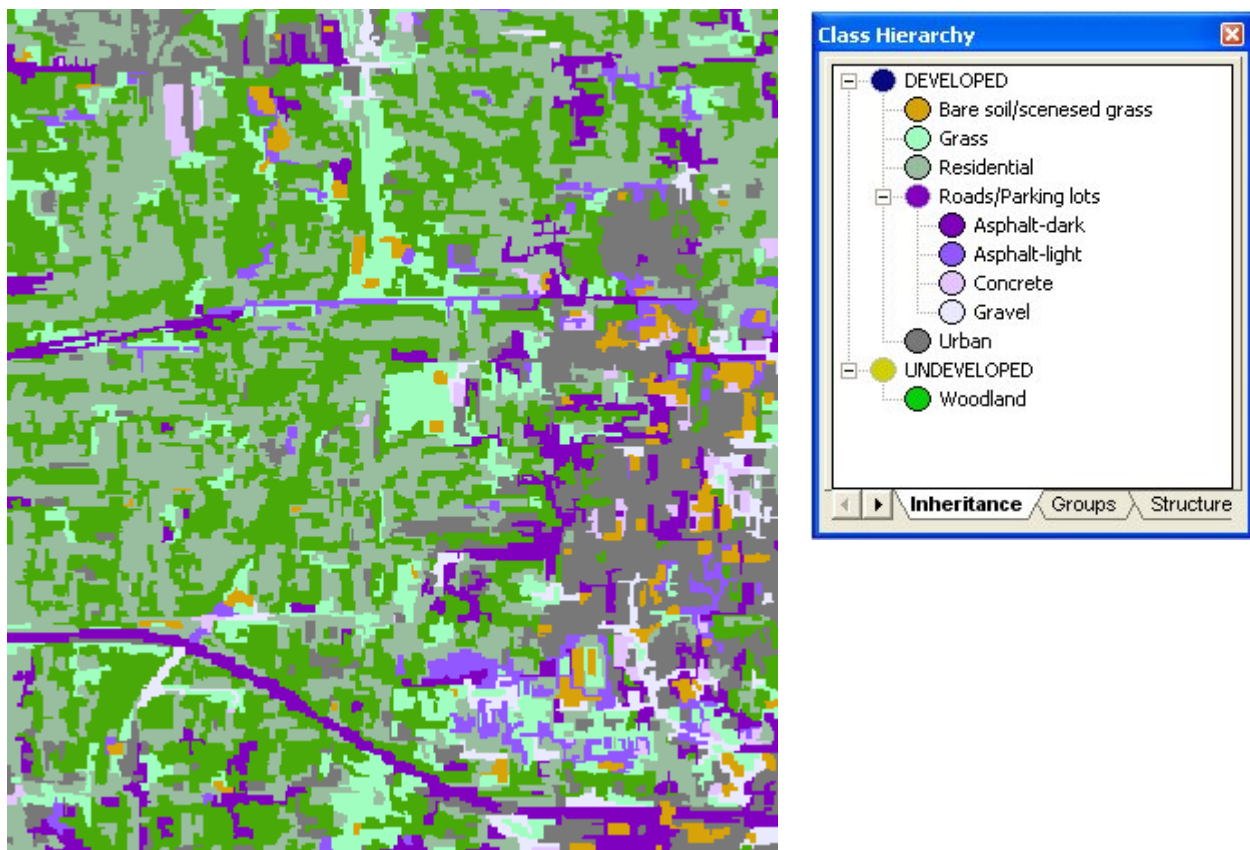


Figure 11. Land cover classification of ATLAS imagery.

The QuickBird image is comprised of 532 x 609 pixels covering 1.28 x 1.46 km. At a resolution of 2.4 m, very small features can be segmented as image objects. However, because QuickBird imagery is limited to four channels, there is not much spectral information to permit a high degree of differentiation. Thus, there is a delicate balance between object size and spectral fidelity. This QuickBird classification was performed at multiple scales. The first order classification is based on the initial or level 1 segmentation in which individual houses and trees were defined and classified. These were then clustered in a second order or level 2 classification (Figure 12). The result is that individual buildings were differentiated based on the type and color of roofing material and several types of road materials were differentiated. In addition, although deciduous and evergreen trees could be distinguished at level 1, a scalar was imposed such that if both types occurred within a segment at level 2, then a Mixed Woodland class could be identified. In classifications of this type, it is conceivable that any number of quantitative parameters could subsequently be determined, such as quantifying the number of houses, or number of house of a certain size. One could also perhaps estimate the total length of roadways within the image. Certainly, the advantage of any image based classification is the manner in which the computer is utilized to yield quantitative information about the classified scene.

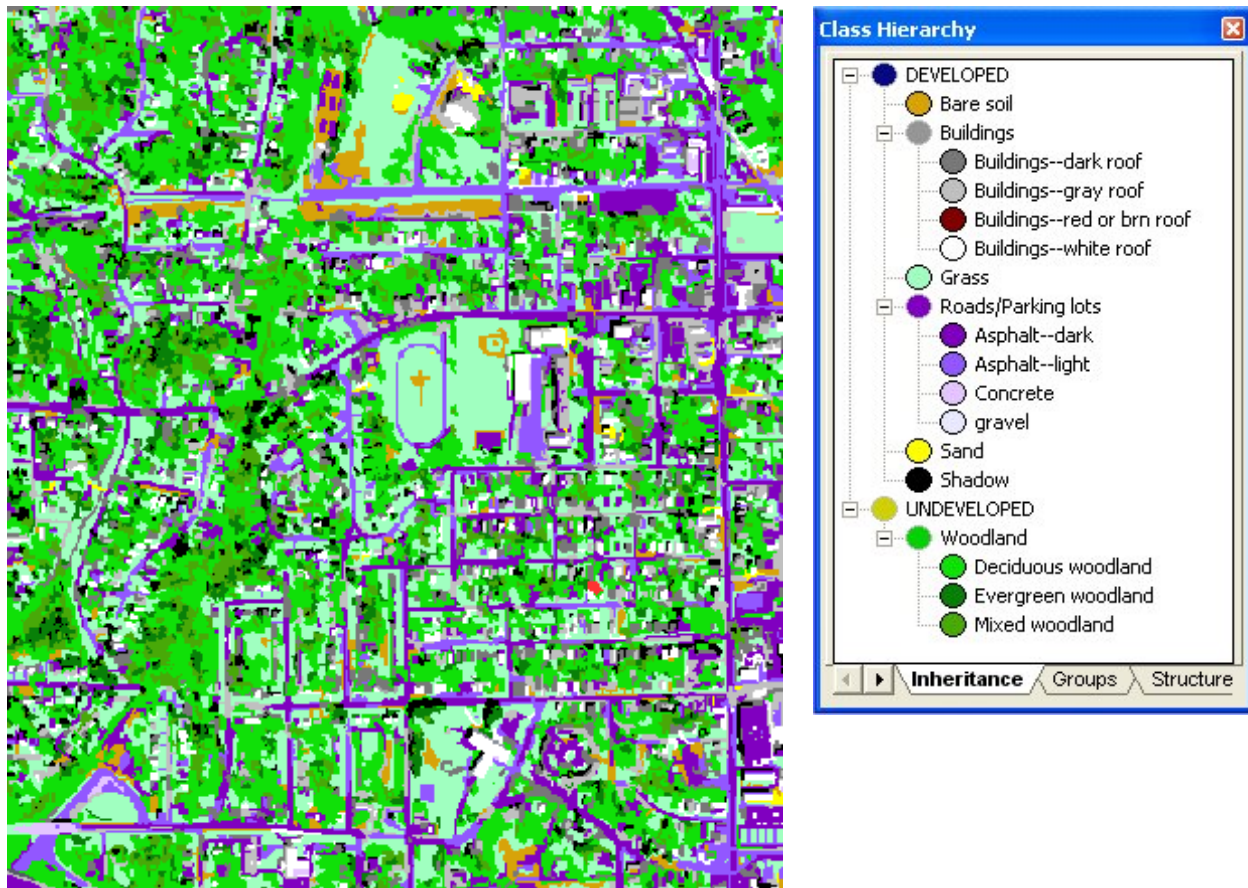


Figure 12. Land cover classification of QuickBird imagery.

11. PROBLEMS AND CHALLENGES

Classification of very high resolution imagery tends to present problems and/or challenges that may or may not be typical while performing similar work with coarser resolution imagery. Some of these difficulties are described here simply to raise awareness for other image analyst. How one deals with the difficulties depends on ones level of competency, familiarity with software capabilities and other resources available.

- Discriminating between light colored asphalt and gray roofed houses. These are largely comprised of the same materials (asphalt shingles or tar paper sheeting on building roofs) and thus yield a similar spectral signature. Classifying asphalt is sometimes further complicated at such high resolution when there is an abundance of automobiles on the road, in parking lots or parked on the shoulder in a residential area. Asphalt is also difficult to classify at high resolution when shadows from tall features (buildings, trees) cast shadows on the road or parking lot. These shadows also have different characteristics depending on the transparency of the obstruction (building vs. tree).
- Transitions between classes are always difficult, but are much more common in high resolution imagery. The problem is exacerbated by the fact that, with the exception of hyperspectral data, high resolution sensors have low spectral resolution. One of the most commonly encountered transitions pertains to discriminating between grass and bare soil. The problem is even greater in winter or early spring imagery with senesced grass. Confusion is common for this leaf-off scene because Bermuda grass is the most commonly used variety for residences, commercial property and golf courses. Public parks are typically covered with a fescue variety of grass that remains green year-round. In March, the Bermuda is still senesced and, where it is thin or sparse, it may be spectrally indistinguishable from sand. In this image, the albedo of sand does not appear to be as high as expected and may, in fact, be wet thereby contributing to the confusion with grass.
- In wintertime imagery, there is often also difficulty in discriminating between senescent grass and deciduous trees, largely because significant contribution to overall radiance from the underlying grass passes through the tree crown when there are no leaves.
- Mixed woodland—the level 1 segmentation scale is so small that individual trees or small clusters are segmented. Consequently, segments with mixed trees are uncommon unless the segment size is increased or multiscale segmentation-based classification is used.

12. CONCLUSIONS

The choices of available imagery are large and expected to increase in the years ahead. As transportation industry leaders turn more and more to satellite-based imagery to address efficiency, one must continuously evaluate specific requirements and choose the correct imagery for the job. Some types of imagery are more readily available and at a lower cost than other imagery options. One should not overlook the potential for lower resolution imagery to satisfy requirements for the sake of higher resolution imagery with the false expectation that it is inherently better. In this activity, we attempt to demonstrate the advantages and disadvantages of

imagery with several different characteristics to develop awareness of these products and the level of competency required to utilize them in transportation industry applications.

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